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The impact of task load on the integration of explicit contextual priors and visual information during anticipation

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Abstract

There is limited knowledge about the impact of task load on experts' integration of contextual priors and visual information during dynamic and rapidly evolving anticipation tasks. We examined how experts integrate contextual priors—specifically, prior information regarding an opponent's action tendencies—with visual information such as movement kinematics, during a soccer-specific anticipation task. Furthermore, we combined psychophysiological measures and retrospective self-reports to gain insight into the cognitive load associated with this integration. Players were required to predict the action of an oncoming opponent, with and without the explicit provision of contextual priors, under two different task loads. In addition to anticipation performance, we compared continuous electroencephalography (EEG) and self-reports of cognitive load across conditions. Our data provide tentative evidence that increased task load may impair performance by disrupting the integration of contextual priors and visual information. EEG data suggest that cognitive load may increase when contextual priors are explicitly provided, whereas self-report data suggested a decrease in cognitive load. The findings provide insight into the processing demands associated with integration of contextual priors and visual information during dynamic anticipation tasks, and have implications for the utility of priors under cognitively demanding conditions. Furthermore, our findings add to the existing literature, suggesting that continuous EEG may be a more valid measure than retrospective self-reports for in-task assessment of cognitive load.

KEYWORDS

cognitive load, decision making, electroencephalography (EEG), soccer

1 | INTRODUCTION

The ability to anticipate an imminent event facilitates successful performance in dynamic and rapidly evolving environments, such as those encountered in many sports (Williams, Ford, Eccles, & Ward, 2011). In soccer, for example, fast and accurate anticipation of an oncoming attacker's next move can be crucial in order for a defender to select and execute an appropriate action in time to prevent a goal-scoring opportunity (Williams, 2000). It is well-known that expert athletes use advance visual information, such as information arising from the movement kinematics of an opponent, during anticipation (e.g., Farrow, Abernethy, & Jackson, 2005; Loffing & Hagemann, 2014; Wright, Bishop, Jackson, & Abernethy, 2013). However, due to advances in technology that enable sophisticated performance analyses, the provision of a priori information about forthcoming opponents has become a prevalent component in the preparation of elite athletes (Memmert, Lemmink, & Sampaio, 2017). Prior sources of information that are relevant to a specific performance context (e.g., an opponent's action tendency) are termed *contextual priors* and can be acquired through task experience (e.g., Loffing, Stern, & Hagemann, 2015; Mann, Schaefers, & Cañal-Bruland, 2014) or explicit task instructions (Seriès & Seitz, 2013).

It has been proposed that Bayesian reliability-based models may provide a suitable framework to elucidate the processes by which athletes integrate contextual priors and visual information during anticipation (Gredin, Bishop, Broadbent, Tucker, & Williams, 2018; Gredin, Broadbent, Williams, & Bishop, 2019; Loffing & Cañal-Bruland, 2017). It is proposed that this integration process, together with the use of top-down attentional control driven by prior knowledge, draws on limited working memory resources (Kaplan & Berman, 2010; De Neys, Schaeken, & D'Ydewalle, 2002; Waldmann & Hagmayer, 2001). In the current study, we examined the impact of a cognitively demanding secondary task on the integration of explicit contextual priors and visual information during anticipation in soccer. Additionally, we combined objective psychophysiological measures electroencephalography (EEG) and retrospective self-reports rating scale mental effort (RSME) to gain insight into the load imposed on working memory during this integration process.

Bayesian theory postulates that people make predictive judgments on the basis of causal probabilistic relationships between known informational variables and unknown to-be-anticipated variables. That is, *if* "*X*" (a known informational variable) occurs, *then* there is a certain probability that "*Y*" (an unknown to-be-anticipated variable) will occur. Individuals weigh up and integrate various informational variables on the basis of their comparative reliability with regard to the to-be-anticipated event (Vilares & Körding, 2011). Such reliability-based integration of explicit contextual priors and visual information was demonstrated in sport by Gredin and colleagues (2018), whereby expert and novice soccer players, in a 2-versus-2 scenario, had to predict an oncoming opponent's action, with and without explicit contextual priors pertaining to the opponent's action tendencies (i.e., pass or dribble). To utilize the priors effectively the players had to integrate the information with evolving visual information—specifically, the positioning of the players off the ball. The expert players integrated contextual priors with environmental information more effectively than novices. The experts altered their allocation of visual attention toward relevant visual information (i.e., the players off the ball) facilitating the effective use of the priors to inform their early anticipatory judgments (i.e., when the reliability of oncoming opponent's kinematics was low), whereas the novices did not. However, in accordance with Bayesian models of probabilistic inference, the biasing effects of the priors decreased closer to the key point of action later in the trial (i.e., as the reliability of the kinematic information from the oncoming opponent increased). Such conditional integration of contextual priors and evolving visual information by expert athletes has also been demonstrated in baseball (Gray & Cañal-Bruland, 2018) and cricket (Runswick, Roca, Williams, McRobert, & North, 2018).

Causal inference of information is deemed to involve semantic memory retrieval processes (De Neys et al., 2002), where increased conditionalization (e.g., integration of a priori probabilistic rules and evolving visual information) leads to increases in processing demands (Waldmann & Hagmayer, 2001). Furthermore, top-down allocation of visual attention, which is driven by the individual's prior knowledge and beliefs (Corbetta & Shulman, 2002), is mediated by the central executive and is therefore deemed to impose greater processing demands than bottom-up, or stimulus-driven, attentional processes (Kaplan & Berman, 2010). Consequently, it could be assumed that using contextual priors to inform anticipation might lead to increases in the load imposed on working memory (referred to as "cognitive load"; Antonenko, Paas, Grabner, & van Gog, 2010). It has been suggested that the total cognitive load is determined by intrinsic load (i.e., the complexity of elements inherent in the task in relation to the level of expertise of the performer; referred to as "task load") and extraneous load (i.e., the way the instructional task is presented; see Sweller, 2010). Since the capacity of working memory is limited (Paas, Tuovinen, Tabbers, & Van Gerven, 2003), research is needed to explore the impact of varying task loads on the use of contextual priors and visual information during anticipation. It may be the case that increased task load reduces available cognitive resources, which would diminish the ability to integrate contextual priors and environmental cues during anticipation. An enhanced understanding of this phenomenon would have practical implications for a wide range of professional domains, in which the practitioner must deal with considerable, not to mention highly variable, task loads (e.g., aviation [Gentili et al., 2014], military combat [Berka et al., 2007], and sport [Abernethy, Maxwell, Masters, Kamp, & Jackson, 2007]).

Runswick and colleagues (2018) tested these assumptions by implementing a backward-counting task, in which skilled and less-skilled cricket batters had to predict the location of bowlers' deliveries, both with and without contextual priors pertaining to the bowler's action tendencies, game state, and field setting. Additionally, the authors used the RSME (Zijlstra, 1993) to collect retrospective ratings of the cognitive load that the batters perceived they had invested in the task. It was predicted, based on cognitive load theory (see de Jong, 2010) and Müller and Abernethy's (2012) model of anticipation in striking sports, that contextual priors would enhance anticipation performance in skilled batters. However, unlike their skilled counterparts, less-skilled batters would not be able to automatically process the contextual information and, as such, contextual priors would lead to increases in cognitive load and impaired performance. In contrast to the predictions, the provision of contextual priors led to enhanced anticipation performance in both skilled and less-skilled batters without affecting their perceived levels of cognitive load. Moreover, the beneficial performance effect of contextual priors was greater when the anticipation task was accompanied by the backward-counting task (i.e., under high task load), compared to when it was not (i.e., under low task load). The authors suggested that combining contextual priors and visual information was governed by automatic processes. It was proposed that the implementation of the secondary backward-counting task may have suppressed conscious control and, as such, facilitated these processes (see also Engström, Markkula, Victor, & Merat, 2017).

These findings contradict the assumption that the integration of contextual priors and visual information would be hampered under more cognitively demanding performance conditions. However, the findings from Runswick and colleagues (2018) may be due to the fact that the batters were able to inform their judgments from the priors alone, without having to integrate them with evolving visual information. For example, the batters did not have to take into account environmental cues that emerged over the course of a trial in order to make use of their a priori awareness of field settings. It is possible that this lack of interplay between contextual priors and evolving visual information allowed for more automatic processing and, as such, reduced the cognitive resources required to use the contextual priors effectively. Alternatively, the self-report data may not provide a valid measure of cognitive load, perhaps instead reflecting perceptions of task difficulty (see Westbrook & Braver, 2015), or may not provide an accurate insight into the temporal fluctuations in cognitive load occurring over time due to varying use of contextual priors over the course of task performance (see Gray & Cañal-Bruland, 2018; Gredin et al., 2018; Runswick, Roca, Williams, et al., 2018). Conversely, psychophysiological measures of continuous cognitive load, such as EEG may provide a more sensitive and objective measure of cognitive load for specific durations during task performance (e.g., average load imposed over the first seconds of a trial; Antonenko et al., 2010).

The continuous EEG signal is composed of oscillations in various frequencies, where power fluctuations within the theta (θ) and alpha (α) frequency bands (typically defined as 4–7 Hz and 8–13 Hz, respectively; Andreassi, 2007) are deemed to reflect changes in cognitive processing demands. Importantly, θ and α oscillations captures changes in cognitive processes, even when the individual is unaware of these changes or is unable to verbalize them (Antonenko et al., 2010). The cortical activity within the θ and α bands have been reported to partly represent different cognitive functions, to be predominant over different scalp regions, and to respond in opposite ways to increased cognitive load. Several researchers have demonstrated a positive correlation between frontal θ activity and the processing demands of vital cognitive functions, such as central executive attentional control, and encoding and retrieval of episodic information (see Hsieh & Ranganath, 2014; Sauseng, Griesmayr, Freunberger, & Klimesch, 2010). While the physiological function of the α rhythm is not fully clear, decreased activity in parietal α is deemed to reflect increased cognitive load (see Antonenko et al., 2010). One explanation as to why the relationship between α oscillations and alterations in cognitive load is unclear may be that the majority of researchers have applied a fixed, broad definition of the α rhythm (e.g., 8–13 Hz) for participants, rather than using narrower bands (e.g., α_1: 8–10 Hz, α_2: 11–13 Hz) based on the individual alpha frequency (IAF) for each participant. While α_1 is deemed to reflect non-task and non-stimulus-specific demands, such as general arousal, activity within the higher α band is related to demands placed on task-specific processes, including stimulus inference and semantic memory retrieval (see Klimesch, 1999).

We adopted the same design employed by Gredin and colleagues (2018), in which expert soccer players were required to predict the direction of an oncoming opponent's actions, either with or without explicit contextual priors regarding the opponent's action tendencies. Furthermore, by adding another condition with contextual priors, in which the players had to perform a secondary n-back task, we assessed the extent to which performance was modulated by increased task load. In addition to anticipation performance, we captured spectral power estimates in frontal θ and parietal α_2 (EEG), as well as retrospective self-reports (RSME) in order to gain novel insight into the cognitive load elicited by each condition. A sample of expert soccer players was used as it has been shown that experts, more so than novices, use explicit contextual priors to inform their allocation of visual attention and anticipation. In line with previous research (e.g., Gredin et al., 2018; Gredin et al., 2019; Navia, Van der Kamp, & Ruiz, 2013), we predicted that the explicit provision of contextual priors would bias anticipatory judgments toward the most likely outcome given the priors. We hypothesized that the biasing impact of priors would enhance anticipation on congruent trials, in which the outcome concurred with the most likely one given the opponent's action tendencies, whereas no meaningful performance effect would be found on incongruent trials (cf. Gredin et al., 2018). We believed, due to the interplay between contextual priors and visual information, that the integration of contextual priors and visual information would not allow for automatic processing. As such, we hypothesized that the explicit provision of contextual priors would increase the cognitive load imposed on players, due to increased causal inference of information and top-down allocation of visual attention (Kaplan & Berman, 2010; De Neys et al., 2002; Waldmann & Hagmayer, 2001).

However, we predicted that this effect would only be manifested in the continuous EEG recordings and not in the measure of self-assessed cognitive load due to the validity of the measures (Antonenko et al., 2010; Gredin et al., 2018). Finally, we expected that increased task load would disrupt the integration of contextual priors and visual information and adversely affect performance, due to a detraction of cognitive resources from the limited capacity of working memory (Paas et al., 2003).

2 | METHOD

2.1 | Participants

Altogether, 17 expert male soccer players (M_{age} = 21 years, *SD* = 1) participated. The players had a mean of 11 years (*SD* = 2) of competitive experience in soccer and took part in an average of 7 hr (*SD* = 3) of practice or match play per week. The sample size was comparable to that employed in previous research using comparable designs to examine anticipation (e.g., Broadbent, Gredin, Rye, Williams, & Bishop, 2019; Gredin et al., 2018; Gredin et al., 2019) and in studies using EEG power spectral estimates to examine the cognitive processes employed during sport-task performance (e.g., Haufler, Spalding, Santa Maria, & Hatfield, 2000; Hillman, Apparies, Janelle, & Hatfield, 2000; Kerick et al., 2001). The study was approved by the Research Ethics Committee of the lead institution and conformed to the recommendations of the Declaration of Helsinki. Written informed consent was obtained from all participants.

2.2 | Test stimuli

The test stimuli were filmed on an artificial turf soccer pitch using a high-definition digital video camera (Canon XF100, Tokyo, Japan) with a wide-angle converter lens (Canon WD-H72 0.8x, Tokyo, Japan). The video camera was attached to a moving trolley, at a height of 1.7 m, to enable replication of the perspective of a central defender in a typical match situation (i.e., facing oncoming opponents while simultaneously moving backward). The video sequences represented 2-versus-2 counter attacking scenarios. In each sequence, there was one attacking player in possession of the ball (referred to as "the opponent"), a second attacker off the ball, and one defender marking the second attacker throughout the sequence. The participant viewed all sequences from a first-person perspective, as if they were the second defender (see Figure 1).

At the start of each sequence, the opponent was positioned approximately 7 m in front of the participant and 3 m inside the halfway line. The attacker off the ball and the marking defender started approximately 3 m behind the opponent on the left or right side. In a match, soccer players are normally aware of the relative positions of the ball and other players; therefore, each sequence started with a freeze-frame of 1 s, to allow the participant to determine this information (cf. Roca, Ford, McRobert, & Williams, 2011). When the sequence started, the players approached the participant and, after approximately 1.5 s, the attacker off the ball made a direction change toward either the left or the right. The sequence lasted for 5 s and, at the end of it, the opponent was positioned approximately 3 m in front of the participant. The attacker off the ball was level with the opponent, either to his left or right. At the end of the sequence, the opponent could either pass the ball to his teammate (33% of the trials) or dribble the ball in the opposite direction (67% of the trials).

In total, 130 separate simulations were created using Pinnacle Studio software (v15; Pinnacle, Ottawa, Canada). Two qualified UEFA A licensed coaches independently selected the clips that they considered representative of actual game play. Only the clips that were selected by both coaches were included in the final test footage. The final test footage comprised 36 video sequences, which were projected at a size

FIGURE 1 Test Stimuli. In each video sequence, there was one attacking player in possession of the ball, a second attacker off the ball, and one marking defender. The participant viewed the sequence from the perspective of the second defender

of 2.1 × 1.6 m onto a projection wall using an Optoma HD20 DLP projector (Optoma, New Taipei City, Taiwan).

2.3 | Task design

The participant was seated 3 m in front of the projection wall and tasked with predicting the direction (left or right) of the opponent's final action. Responses were recorded via two handheld response devices; one for "left" and one for "right" responses, held in the left and right hands, respectively. The participant was instructed to respond quickly and accurately. Immediately after the participant's response, the sequence was occluded and feedback for response time and accuracy was displayed on-screen. If the participant responded 120 ms or more after the foot-ball contact of the opponent's final action, then the trial was counted as incorrect (cf. Gredin et al., 2018).

2.4 | Procedure

Prior to testing, the participant was given an overview of the experimental protocol and donned a portable EEG system (see details below). Thereafter, continuous EEG data were recorded over a pretest period of 2 min, during which the participants were encouraged to stay seated in a comfortable position with their eyes closed while avoiding any head or body movements. The participant then performed four familiarization trials in order to become acquainted with the experimental setup and response requirements. The 36 test trials were then presented under three different conditions (i.e., 108 test trials in total): CTRL; EXP; and EXP^{TL}. At the beginning of each condition, the participant performed five condition-specific familiarization trials, after which the 36 test trials were presented in 3 blocks of 12 trials each. In both EXP and EXP^{TL}, contextual priors (i.e., information about the opponent's action tendencies; dribble = 67%, pass = 33%) were explicitly provided prior to each block, both verbally and on-screen. In order to increase the cognitive load in EXP^{TL}, the task load was manipulated using a secondary *n*-back task: After four randomly selected trials within each block, the participant had to indicate the direction of the final action two trials previous. To maintain engagement with both tasks, the participant was instructed that the responses on the secondary task were equally important as those for the primary anticipation task. In CTRL, no secondary task was performed, and no contextual priors were explicitly provided (NB: the proportion of trials where the attacker in possession dribbled [67%] and passed [33%] the ball was the same as in the two experimental conditions). The order in which conditions were presented was counterbalanced across participants to minimize the influence of potential learning and carryover effects across conditions (cf. Gray, 2009; Jackson, Ashford, & Norsworthy, 2006; Runswick, Roca, Williams, Bezodis, & North, 2017). To eliminate the influence of trial-specific characteristics, the same 36 trials were presented across all three conditions. However, to avoid any potential familiarity effects across conditions, the trial order in each condition was randomized.

Response time and accuracy were recorded for each trial via the button press response. We recorded continuous EEG data for each condition, and the EEG trace was automatically tagged with event markers that indicated stimulus onset. The participant was encouraged to remain still and to avoid eye blinks, where possible, during the task. Upon completion of each condition, the participant was asked to state, using the RSME (Zijlstra, 1993), their perception of the level of cognitive effort they had expended in order to perform the trials in the preceding condition. The test session took 90 min.

2.5 | EEG recording and processing

The EEG data were recorded using a portable "EEGo Sports" EEG system (ANT Neuro, Enschede, Netherlands) with 32 Ag/AgCl electrodes arranged according to the international 10–20 system (including left and right mastoids, CPz as reference, and AFz as ground; Jasper, 1958). Impedances were kept below 10 kΩ, and the sampling rate was set to 500 Hz. A bandpass filter setting of 0.1–100 Hz and a 60–Hz notch filter was applied during the recording to avoid electrical interference and muscle artifacts.

The data were processed offline using Brainstorm (Tadel, Baillet, Mosher, Pantazis, & Leahy, 2011), which is freely downloadable under the GNU public license (https://neuroim-age.usc.edu/brainstorm). The signal was re-referenced to linked mastoids, and then, submitted to a high-pass (0.5 Hz) and low-pass (30 Hz) filter to reduce low- and high-frequency noise, respectively. Ocular artifacts were further identified and corrected using independent component analysis (ICA) in line with the guidelines provided by Dickter and Kieffaber (2014). After the ICA procedure, the continuous data file was partitioned into single epochs of 2,300 ms. The conditions were epoched into 36 single trials beginning 200 ms after stimulus onset and ending 2,500 ms after stimulus onset. This time window was chosen to include the stage of the trial during which the participants were predicted to be particularly reliant on contextual priors (Gredin et al., 2018). The pretest baseline period was epoched into 36 successive segments to match the number of trials in the test conditions. Each trial was visually inspected for residual artifacts and contaminated trials were discarded from subsequent analyses. Decisions about rejecting individual epochs were made by an experimenter, who was blind as to the condition to which they belonged. Arbitrary amplitude thresholds for artifact rejection were not used (Meltzer, Negishi, Mayes, & Constable, 2007).

Contaminate-free segments from the pretest baseline period and each condition (average = 32, minimum = 25, and maximum = 36) were submitted to a Fast Fourier Transformation to transform the time-course signal into power estimates for different wave frequencies. Power estimates were averaged across trials so that separate averages were obtained for the baseline period and each test condition. Average power estimates in the test conditions were then grouped into individualized θ and α_2 frequency bands. Individualized frequency bands were used, as fixed bands may blur specific relationships between cognitive performance and power measurements (Klimesch, 1999). The frequency-band borders were determined using the IAF for each participant as an anchor point. The IAF was determined by visual inspection of the average peak α frequency (i.e., the maximum power value within the α band) over the baseline period; θ = IAF −6 Hz to IAF − 2.5 Hz, α_2 = IAF to IAF + 2.5 Hz (Pavlov & Kotchoubey, 2017). Spectral power estimates were obtained for frontal midline (Fz) and parietal midline (Pz) electrodes, as these are deemed to be the most sensitive sites when monitoring cognitive load via cortical activity within the θ and α frequency band, respectively (Scharinger, Soutschek, & Schubert, 2015). All data were log-transformed to reduce bias arising from nonuniformity of error.

2.6 | Dependent measures

2.6.1 | Anticipation performance

To assess the participant's reliance on the opponent's action tendencies, and to demonstrate the appropriateness of our study design when using explicit contextual priors as a manipulation, the dribble-to-pass ratio in each condition was calculated. Additionally, anticipation performance was expressed by the time and accuracy of the participant's button responses on each trial. As previous research has shown that contextual priors have different effects on congruent and incongruent trials (Broadbent et al., 2019; Gredin et al., 2018), trials in which the opponent dribbled the ball (i.e., congruent trials) and trials in which the opponent passed the ball (i.e., incongruent trials) were analyzed separately.

2.6.2 | Cognitive load

Our primary measure for cognitive load was defined by the spectral power ratio between frontal θ and parietal α_2 (Fz θ/Pz α_2), where amplified power ratio indicated an increase in cognitive load (cf. Fuentes et al., 2018; Holm, Lukander, Korpela, Sallinen, & Müller, 2009; Jaquess et al., 2017; Postma & Schellekens, 2005). The frontal θ to parietal α ratio has successfully been used to measure the overall cognitive load placed on working memory during task performance (e.g., Fuentes et al., 2018; Holm et al., 2009; Jaquess et al., 2017; Postma & Schellekens, 2005) and is deemed to be more sensitive to changes in cognitive load than absolute spectral power (Holm et al., 2009). We restricted our analyses to α_2, to avoid non-task and non-stimulus-specific demands associated with lower α frequencies from violating the cognitive load index (Klimesch, 1999). In order to trace the mechanisms underpinning such changes, we analyzed the absolute spectral power in Fz θ and Pz α_2, separately.

Self-assessed levels of cognitive load were expressed as the RSME score reported for each condition (cf. Brouwer et al., 2012; Cocks, Jackson, Bishop, & Williams, 2016; Runswick et al., 2017). The scale ranges from 0 to 150 and contains nine descriptors; higher ratings indicate higher levels of perceived cognitive load (e.g., 2 = absolutely no effort; 58 = rather much effort; 113 = extreme effort).

2.7 | Statistical analysis

Descriptive statistics are reported as means and *SD*s. *p* values were calculated for both tails of the distribution of the statistic and each *p* value represents the probability of observing either a positive or negative value equal to or more extreme than the observed value, if the true value is null (Cumming, 2012). We decided not to use traditional null-hypothesis significance testing (Neyman & Pearson, 1933) in favor of interpreting the point estimates and their 95% confidence intervals against threshold values for meaningful effects. The latter approach was chosen as it is more informative to report and discuss the magnitude of observed effects and precision of estimates, than whether observed effects are statistically significant according to a specified alpha level (e.g., $p < .05$; Cumming, 2014; Wasserstein, Schirm, & Lazar, 2019; Wilkinson, 2014). Magnitudes of observed effects are reported as standardized (d) and unstandardized units. The standardized effects were assessed by dividing the mean effect by the combined *SD* (Cumming, 2012). In the absence of data allowing for prior statistical quantification of what would constitute effect thresholds for our outcome measures, observed effects were reported according to the following scale: $0.2 > |d|$, trivial; $0.2 \leq |d| < 0.5$, small; $0.8 \leq |d|$, large (Cohen, 1988). Cohen's standardized unit for the smallest worthwhile effect (0.2) was used as a threshold value when estimating uncertainties in the true effects to be meaningfully negative, trivial, or meaningfully positive (Cumming, 2012; Winter, Abt, & Nevill, 2014). In order to facilitate the report and discussion of the confidence in our results, the following scale was used to convert the quantitative uncertainties to qualitative descriptors: <0.5%, most unlikely; 0.5%–5%, very unlikely; 5%–25%, unlikely; 25%–75%, possible; 75%–95%, likely; 95%–99.5%, very likely; >99.5%, most likely (Hopkins, 2002). If the lower and upper bounds of the confidence interval exceeded the thresholds for the smallest meaningfully negative and positive effect, then the effect was deemed unclear. All other effects were reported as the magnitude of the observed value and were evaluated probabilistically as described above (Batterham & Hopkins, 2006; Wilkinson, 2014).

3 | RESULTS

3.1 | Anticipation performance

As shown in Figure 2, the dribble-to-pass ratio was lower in CTRL than in EXP ($d = 0.61 \pm 0.57$, $p = .036$) and EXP^{TL} ($d = 0.68 \pm 0.62$, $p = .035$), whereas no clear effect was revealed between EXP and EXP^{TL} ($d = 0.27 \pm 0.54$, $p = .229$). Table 1 shows the unstandardized effects for dribble-to-pass ratio across conditions. Analyses of response accuracy on congruent trials yielded higher response accuracy in EXP than in CTRL ($d = 0.30 \pm 0.40$, $p = .136$), but no clear effects were obtained when EXP^{TL} was compared to CTRL ($d = 0.19 \pm 0.45$, $p = .390$) and EXP ($d = 0.11 \pm 0.45$, $p = .614$). On incongruent trials, response accuracy was lower in EXP^{TL} compared to in CTRL ($d = 0.36 \pm 0.51$, $p = .153$), while no clear effect was revealed between EXP and CTRL ($d = 0.12 \pm 0.75$, $p = .731$) or between EXP and EXP^{TL} ($d = 0.32 \pm 0.54$, $p = .229$). The unstandardized effects for response accuracy across conditions are presented in Table 1. Analyses of response time revealed only trivial effects across conditions, both on congruent (EXP versus. CTRL, $d = 0.12 \pm 0.10$, $p = .028$; EXP versus. EXP^{TL}, $d = 0.06 \pm 0.14$, $p = .431$; EXP^{TL} versus. CTRL, $d = 0.06 \pm 0.15$, $p = .408$) and incongruent (EXP versus. CTRL, $d = 0.15 \pm 0.14$, $p = .036$; EXP versus. EXP^{TL}, $d = 0.08 \pm 0.25$, $p = .492$; EXP^{TL} versus. CTRL, $d = 0.08 \pm 0.17$, $p = .339$) trials. The descriptive statistics for response time and accuracy in each condition is presented in Table 2.

3.2 | Cognitive load

As shown in Figure 2, our primary analysis of cognitive load showed that the Fz θ/Pz α_2 ratio was higher in both EXP and EXP^{TL} compared to CTRL ($d = 0.20 \pm 0.19$, $p = .037$ and $d = 0.38 \pm 0.22$, $p = .002$, respectively), but no meaningful effect was obtained between EXP and EXP^{TL} ($d = 0.17 \pm 0.19$, $p = .075$). Separate comparisons of the

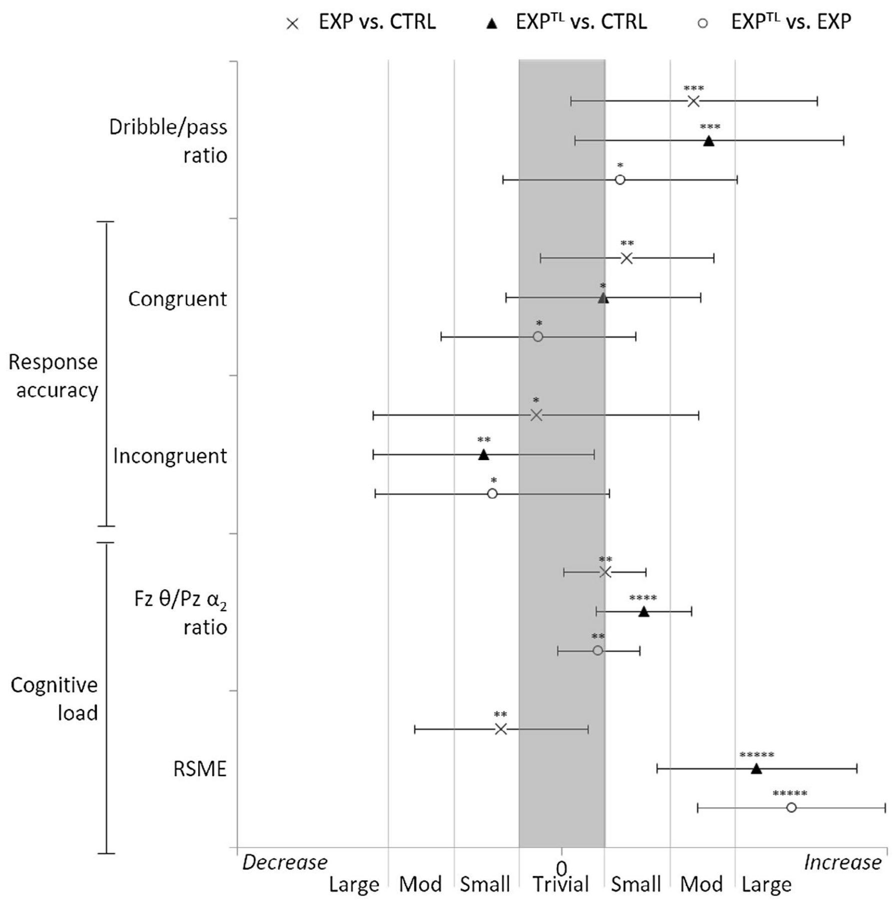

FIGURE 2 Within-Participants Effects for Response Accuracy, Fz θ/Pz α_2 ratio, and RSME score across conditions. Standardized effects and 95% confidence intervals, as well as inferences of observed and true effects Inference of observed effect: $0.2 > |d|$, trivial; $0.2 \leq |d| < 0.5$, small; $0.5 \leq |d| < 0.8$, moderate (Mod); $0.8 < |d|$, large. Inference of uncertainty in true effect to have the same sign as the observed effect: * unclear, **possibly (25%–75%); **** very likely (95%–99.5%); ***** most likely (>99.5%)

TABLE 1 Unstandardized effects ($M \pm 95\%$ CI) for dribble/pass ratio, response accuracy, Fz θ/Pz α_2 ratio, and RSME score across conditions

	EXP versus. CTRL	EXP^{TL} versus. CTRL	EXP^{TL} versus. EXP
Anticipation performance			
Dribble/pass ratio	1.2 ± 1.1	2.1 ± 2.0	0.9 ± 1.8
Response accuracy (%)			
Congruent	4.7 ± 6.3	2.9 ± 7.1	−1.7 ± 7.1
Incongruent	−2.0 ± 9.8	−6.9 ± 9.7	−4.9 ± 8.3
Cognitive load			
Fz θ/Pz α_2 ratio	0.5 ± 0.3	0.8 ± 0.4	0.3 ± 0.4
RSME score	−6.0 ± 7.2	18.1 ± 7.7	24.1 ± 9.4

TABLE 2 Descriptive statistics ($M \pm SD$) for response time and accuracy in each condition

	CTRL	EXP	EXP^{TL}
Response time (ms)			
Congruent	4,522 ± 561	4,434 ± 609	4,473 ± 537
Incongruent	4,418 ± 853	4,414 ± 640	4,403 ± 731
Response accuracy (%)			
Congruent	80 ± 15	85 ± 15	83 ± 15
Incongruent	43 ± 19	41 ± 11	36 ± 18

absolute power estimates revealed that the Fz θ power was higher in EXP^{TL} than in EXP ($d = 0.30 \pm 0.15$, $p = .001$) and CTRL ($d = 0.33 \pm 0.17$, $p = .001$), whereas no meaningful effect was yielded between EXP and CTRL ($d = 0.01 \pm 0.14$, $p = .827$). With regard to the absolute power estimates in Pz α_2, only trivial effects were found across conditions (EXP versus. CTRL, $d = 0.16 \pm 0.14$, $p = .027$; EXP versus. EXP^{TL}, $d = 0.06 \pm 0.17$, $p = .472$; EXP^{TL} versus. CTRL, $d = 0.10 \pm 0.16$, $p = .204$). The retrospective self-reports of cognitive load yielded a lower RSME score in EXP compared to CTRL ($d = 0.28 \pm 0.40$, $p = .165$) and EXP^{TL} ($d = 1.06 \pm 0.50$, $p = .001$), and a higher RSME score in EXP^{TL} compared to CTRL ($d = 0.90 \pm 0.46$, $p = .001$; see Figure 2). Table 1 shows the unstandardized effects for Fz θ/Pz α_2 ratios and RSME scores across conditions.

4 | DISCUSSION

We examined the impact of task load on experts' integration of contextual priors and visual information during a rapid dynamic anticipation task. Furthermore, we combined objective psychophysiological measures (EEG) and retrospective self-reports (RSME) to elucidate the cognitive load associated with this integration process.

As predicted, our findings support previous research demonstrating that explicit contextual priors bias experts' anticipatory judgments toward the most likely outcome given the priors (e.g., Gredin et al., 2018, 2019; Navia et al., 2013). This effect was manifested in a likely increase in the dribble-to-pass ratio in EXP relative to CTRL. In line with predictions, the provision of priors resulted in enhanced performance on congruent trials, expressed by a possible higher response accuracy in EXP than in CTRL, whereas no clear effect was found on incongruent trials. Findings replicate those reported by Gredin and colleagues (2018) who used a comparable study design and a similar sample of participants, which increases the certainty associated with our results. Our findings provide further evidence that explicit contextual priors facilitate anticipation on congruent trials—that is, when the outcome corresponds with the priors. On incongruent trials, it seems that expert soccer players redefine their context-driven expectations when conflicting kinematic cues from the opponent emerge (see also Broadbent et al., 2019; Gredin et al., 2018). This assumption is in line with the suggestion that experts may use Bayesian reliability-based strategies to integrate explicit contextual priors with evolving visual information during anticipation (Loffing & Cañal-Bruland, 2017).

The beneficial effects on response accuracy observed for congruent trials in EXP relative to CTRL was not replicated in the CTRL-EXP^{TL} comparison. In line with our predictions, increased task load may supress the performance-enhancing effects of explicit contextual priors during anticipation. This proposition contradicts the findings reported by Runswick and colleagues (2018), who showed that increased task load amplified the beneficial effects of contextual priors on cricket batters' anticipation. Runswick and colleagues (2018) argued that the cognitively demanding secondary task may have limited explicit conscious control and as such allowed more efficient automatic processing, which could explain the superior impact of priors reported under conditions of high task load. However, it should be noted that the batters were primed with various sources of contextual information (i.e., field settings, previous action sequences, and game state) that may have been integrated using more automatic processes than the priors used in the current study. Furthermore, unlike the study by Runswick and colleagues (2018), the players in the current study had to integrate contextual priors with emerging visual information (i.e., the trajectory of the run from the attacker off the ball) in order to make use of the priors. This dynamic interplay between priors and visual information may have required more conscious and effortful integration processes, resulting in less effective use of the priors when the anticipation task was accompanied with a cognitively demanding secondary task.

The assumption that increased task load may impair integration of contextual priors and evolving visual information receives further support from the analyses of incongruent trials. In contrast to our predictions, and unlike the comparison between CTRL and EXP, we found a possible decrease in response accuracy when comparing CTRL and EXP^{TL}. This finding suggests that the secondary *n*-back task reduced players' available cognitive resources; resources that were needed, to integrate and update the contextual priors with conflicting kinematic cues on incongruent trials (Gredin et al., 2018). However, given the uncertainty associated with our results and the lack of replicated findings, more research is needed to confidently suggest that increased task load disrupts the integration of contextual priors and visual information and adversely affects anticipation. In future, researchers should seek to elucidate the extent to which the effects of increased task load may be dependent on the interdependency of priors and unfolding visual information. Such further insight would build on the findings from the present study and could pose important implications for the efficacy of contextual priors under various performance conditions (Abernethy et al., 2007; Berka et al., 2007; Gentili et al., 2014). No meaningful effects on response times were found across conditions, which suggests that the effects on response accuracy were not accompanied with changes in the amount of visual information the players were exposed to before responding on the anticipation task.

We used continuous EEG and self-report measures to obtain insight into the cognitive load associated with the various conditions. In line with our predictions, the EEG data suggest that using explicitly provided contextual priors increased the cognitive load imposed on players (e.g., Holm et al., 2009; Jaquess et al., 2017; Postma & Schellekens, 2005). This suggestion is based on the discrepancy in dribble-to-pass response ratio that was revealed between CTRL and EXP, and the possible increase in spectral power ratio between frontal θ and parietal α_2 when the two conditions were compared. In order to gain an insight into the demands placed on specific cognitive functions during task performance, we analyzed absolute spectral power in frontal θ and parietal α_2 separately. We did not observe any meaningful effect on absolute parietal α_2 power, which was contrary to our predictions. However, probabilistic inference of our results revealed a possible decrease parietal α_2 in EXP compared to CTRL; an effect that has been linked to increased processing demands related to inference of task-specific information and semantic memory retrieval (Klimesch, 1999). These processes are associated with Bayesian strategies for information integration, where predictive judgments are made according to conditional inferences of certain *if-then* relationships known to the person (Clark, 2013; De Neys et al., 2002). In the present study, an informative *if-then* relationship was that of the positioning of the attacker off the ball. That is, *if* the attacker off the ball was positioned to the left of the attacker in possession, *then* it was more likely that the direction of the final action would be to the right, given the opponent's action tendencies. Gredin and colleagues (2018) reported that the explicit provision of contextual priors increased expert players' reliance on this relationship which, in turn, biased their ongoing expectations during performance. The effect on parietal α_2 reported in the current study partially supports these findings and indicates that such propositional inference may bring about increases in cognitive load. However, it is worth noting that, while the qualitative inferences suggested a possible decrease in parietal α_2 power, the observed effect obtained in the current experiment was trivial. Therefore, the presence of an absolute power decrease in parietal α_2 should be inferred with some caution.

In contrast to our predictions, absolute frontal θ power was not higher in EXP than CTRL. The very unlikely power increase in frontal θ that was revealed in the current study was somewhat surprising, since Gredin and colleagues (2018), using the same test stimuli, reported that explicit contextual priors increased the time that expert soccer players spent looking at context-relevant information during the first half of the trial. The authors suggested that the explicit provision of contextual priors promoted top-down control of visual attention, which is purported to correlate positively with frontal θ spectral power, due to the processing demands placed on the central executive (Hsieh & Ranganath, 2014; Sauseng et al., 2010). An explanation for the trivial effect on frontal θ could be that, in contrast to Gredin and colleagues' (2018) study, the players in the current study had to remain seated and were instructed to avoid any type of body movements during performance; this design inevitably reduced the real-world representativeness of the action requirements of the task. It has been argued that action fidelity may be important in order to invoke representative gaze behavior (Dicks, Button, & Davids, 2010). Thus, under the controlled laboratory conditions employed in this study, it may be that the explicit provision of contextual priors did not promote top-down control of attention, as may be the case in more lifelike settings. In future, researchers should combine EEG and eye-tracking data to explore the relationship between attentional control and central executive processing demands during naturalistic anticipation tasks.

In contrast to the EEG findings, and to our predictions, we found a possible decrease in retrospective self-reports of cognitive load when comparing CTRL to EXP. This finding contradicts previous research using the RSME that did not report any differences when contextual priors were provided (e.g., Broadbent et al., 2019; Gredin et al., 2018; Runswick, Roca, Mark Williams, et al., 2018). This finding questions the reliability and validity of RSME as a measure of cognitive load. It has been suggested that retrospective ratings of cognitive load may not accurately capture temporal fluctuations in cognitive load during task performance (Antonenko et al., 2010). For the current task, researchers have shown that the impact of contextual priors is greater over the first half of the trial, whereas players rely more on kinematic information arising from the opponent in later stages (Gredin et al., 2018). It may be that the temporal impact of explicit contextual priors on cognitive load was being overlooked when players were asked to report an aggregated cognitive load score invested in the task after each test condition. This explanation is supported by existing literature, which suggests that continuous EEG may capture changes in cognitive load of which the individual is unaware and unable to verbalize (Antonenko et al., 2010). However, this latter suggestion does not explain the decrease in self-reported cognitive load when contextual priors were explicitly provided, compared to when they were not. Given the additional task-relevant information afforded by the priors, along with enhanced performance, an alternative explanation is that self-reports reflected a perception of task difficulty, rather than the cognitive resources invested in completing the task. Although the two concepts are closely related, task difficulty is determined by the quality and/or volume of information available to solve the task, rather than the individual's cognitive resources. As such, the task can be perceived as less difficult (e.g., in the presence of additional task-relevant information), but at the same time be more cognitively demanding (e.g., increased working memory usage, in order to process additional information), and vice versa (see Westbrook & Braver, 2015). In other words, it may be the case that the players perceived and reported task difficulty to be lower in EXP, in which they were informed about the opponent's action tendencies and performed better, relative to CTRL. Alternatively, the players may have felt that they did not need to devote as much cognitive resources to visual information processing when they received additional information about the opponent's action tendencies, which could explain why total cognitive load was perceived as lower in EXP than in CTRL. In future, researchers should examine the reliability and validity of retrospective self-report techniques such as the RSME, across a variety of tasks, to ensure that they provide a bona fide measure of cognitive load.

Both EEG measures and self-reports suggest that cognitive load increased when the players had to perform the secondary *n*-back task in addition to the primary anticipation task, which suggests that the task load manipulation was successful. Analyses revealed a most likely increase in RSME score and a very likely increase in frontal θ to parietal α_2 ratio between CTRL and EXP^{TL}. For absolute spectral power, we found a likely increase in frontal θ, whereas no meaningful effect was found on parietal $\alpha_{2,}$ when the two conditions were compared. The increased frontal θ activity suggests that greater encoding and retrieval of episodic information occurred, which aligns with findings from previous research in which the *n*-back paradigm has been used as a task load manipulation (Hsieh & Ranganath, 2014; Sauseng et al., 2010). Unlike the findings in EXP, where a possible decrease in parietal α_2 was found, inferences suggested an unlikely decrease in parietal α_2 power when EXP^{TL} was compared to CTRL. This finding implies that fewer cognitive resources were devoted to inference of task-specific information and semantic memory retrieval (Klimesch, 1999) which, in turn, suggests reduced assimilation of contextual priors in EXP^{TL} (De Neys et al., 2002; Waldmann & Hagmayer, 2001).

In summary, our novel findings suggest that increased task load may disrupt the integration of explicit contextual priors and evolving visual information, leading to impaired anticipation performance in dynamic and rapidly evolving environments. By combining performance data with multiple measures of cognitive load, we provide evidence that this effect may be due to the cognitive demands of this integration process. Applied practitioners should be cautious when providing explicit contextual priors to expert performers as this may not always be beneficial to performance, depending on the demands of the task. In future, researchers should seek to replicate and extend these findings in order to provide valuable insight into the effectiveness of explicitly provided contextual priors under cognitively demanding performance conditions. Furthermore, the contradictory findings from EEG and self-report measures of cognitive load have implications for future determination of cognitive load. Namely, our findings add to the existing literature, suggesting that continuous EEG measures enable objective in-task assessment of cognitive load; something that may not be captured by retrospective self-reports (Antonenko et al., 2010).

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